Renewable and Sustainable Energy Reviews 16 (2012) 1399–1411

Contents lists available at SciVerse ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Stochastic techniques used for optimization in solar systems: A review

Naveen Sharma*, Varun, Siddhartha

Department of Mechanical Engineering, National Institute of Technology, Hamirpur, HP 177005, India

ARTICLE INFO

Article history:
Received 8 April 2011
Accepted 9 November 2011
Available online 16 January 2012

Keywords:
Solar systems
Optimization
Stochastic
Deterministic
System performance

ABSTRACT

Nowadays, optimization of solar systems is used to reduce system total cost, increased life cycle savings and improving thermal efficiency. It is very demanding for optimal utilization of solar resources to meet the energy demands. Various optimization techniques either deterministic or stochastic are implemented to achieve this objective. The stochastic techniques generate better results as compared to deterministic in large search space in low computation time. The optimal set of design and operating parameters are means to produce maximum system performance. This study includes review of various stochastic optimization techniques implemented in solar energy systems for performance enhancement. Based on the results given by various investigators, an attempt has been made to compare the stochastic optimization techniques in terms of providing maximum system performance of different solar systems.

Contents

* Corresponding author. Tel.: +91 9882378164; fax: +91 1972223834.
E-mail addresses: sharma.naveen28@yahoo.com (N. Sharma), varun7go@gmail.com (Varun), sid_nitk@yahoo.co.in (Siddhartha).

1364-0321/$ – see front matter
doi:10.1016/j.rser.2011.11.019

1. Introduction

In today's scenario lifestyles needed a continuous and reliable supply of energy due to which energy consumption is expected to double globally during the first half of the twenty first century [1]. Nowadays, the level of a country's development and quality of life is measured in terms of the per capita energy consumption. To fulfill the energy demand, excessive fossil fuel energy is used. This not only cause severe and growing damage to environment from emissions of anthropogenic gases such as carbon dioxide, methane and nitrous oxide, but also bring political crises to countries in terms of global resource conflicts and food shortages. Energy conversion systems based on renewable energy technologies use the Sun's energy in direct and indirect form (solar radiation, wind, falling water, and various plants; i.e., biomass) as the resources to produce energy and seen to be cost effective and have a beneficial impact on the environmental, economic, and political issues of the world. These resources have massive energy potential; however, they are generally diffused and not fully accessible but nowadays, significant progress is achieved by improving the collection and conversion efficiencies, lowering initial and maintenance costs, and increasing the reliability and applicability of renewable energy systems. Solar and other forms of renewable energy offer a practical, clean, and viable solution to growing environmental and energy challenges.

Worldwide research and development in the field of renewable energy resources and systems has been carried out during the last two decades. At the end of 2001 the total installed capacity of renewable energy systems were found to be 9% of the total electricity generation. Using the renewable energy intensive scenario, the global consumption of renewable sources by 2050 would reach 318 EJ [2]. Solar thermal systems are non-polluting and offer significant protection of the environment by reducing greenhouse gas pollution. Therefore, solar thermal systems should be employed to achieve a sustainable future. The amount of sunlight reaching the earth's atmosphere continuously is 1.75×10^5 TW having 60% transmittances through the atmospheric cloud cover and 1.05×10^5 TW reaches the earth's surface continuously. If the solar radiation intensity on only 1% of the earth's surface could be transformed into electric energy with a 10% efficiency, it would produce a resource base of 105 TW, while the total global energy requires for 2050 are estimated to be about 25–30 TW. The present state of solar energy systems are such that single solar cell efficiencies have reached over 20%, with concentrating photovoltaics (PVs) at about 40% and solar thermal systems provide efficiencies of 40–60%. The costs of solar PV panels have come down from about \$30/W to about \$3/W in the last three decades. As a result, the worldwide growth in PV production has averaged more than 30% per year during the last five years [3]. The first solar technology that demonstrated its grid power potential was the solar thermal power using concentrating solar collectors having capacity of 354 MW and is operating continuously in California since 1985. Nowadays, progresses in the area of optimization of solar systems using various deterministic and stochastic techniques have been carried out to achieve the optimum thermal performance and the design and operating parameters.

The tendency to search for the best solution under specified constraints is called optimization. In recent decades, the need for method which lead to an improvement in the systems performance by seeking optimum design and operating parameters are collectively called methods of optimization. The optimization algorithms were divided into six categories as shown in Fig. 1 [4]. In this article, a review on various stochastic techniques used in solar systems for optimization has been carried out.

2. Solar thermal systems

Nowadays, solar thermal technologies utilization increases with a rapid pace due to scarcity of fossil fuels, which uses solar energy either directly or indirectly. The classification of solar thermal systems on the basis of application is shown in Fig. 2. Thirugnanasambandam et al. [5] discussed about the study, design and development of the different solar systems. The various authors reviewed different solar thermal systems such as solar dryers [6–8], solar cookers [9], solar desalination systems [10], solar stills [11] and simulation of solar heating systems [12] on the basis of applications. The main parameters on which the thermal performance of the various solar thermal systems depend upon are shown in Table 1.

3. Simulation of solar systems

Researchers and scientists continuously find the optimum thermal performance of the solar thermal systems with optimal set of design and operating parameters. These results were obtained using different optimization techniques. The classification of various deterministic and probabilistic techniques is shown in Fig. 3 [13].

3.1. Solar air heater

Rao and Suri [14] proposed a simple method to design optimum flat-plate collector area for heating 30 gallons of water per day at latitude of 29.5°N from 43 to 125 °F, in winter at Roorkee is 28 ft^2. Tzafestas et al. [15] describe the transient performance of solar water heater by adjusting heat exchanger in the hot water tank. The results are expressed in form of finite difference equations and the parameters of model are identified using regression analysis of experimental data and then theoretical results are simulated and compared with the experimental results. Klein et al. [16] developed a simulation model to estimate the thermal performance of space and water heating systems for the residences. In this paper, simulation carried for four systems at hourly basis for duration of 8 years considering meteorological data for Madison, Wisconsin and the average performance for 8 years compared with performance of an average year. The results show that an error of 10–15 m^2 in the estimation of optimum collector size has a little effect on cost of solar heating.

Klein et al. [17] developed a simulation model for solar heating systems using air as the heat transfer media incorporating a flat plate air heater and packed bed thermal storage. The simulation results with packed bed having storage capacity per equivalent area is varied from 200 to 1600 kJ/(m^2 °C) indicate that performance of liquid based system is slightly more than air heating system. Chang and Minardi [18] examined optimum collector area which is directly related to both economic factors and system parameters for solar heating systems using TRNSYS program [19]. Duffie and Beckman [20] presented a list of library program for different components, simulation studies for various solar heating processes and various modules for TRNSYS modular program. The various simulation techniques used for simulation of solar heating systems was elaborated by Nafey [12]. Different techniques other than stochastic are also implemented in case of solar air heater such as second law optimization [21,22], mathematical optimization techniques [23] and experimentation [24] carried out by the authors in order to estimate the thermal performance. Rabl et al. [25] for the optimization of parabolic trough collectors and explained by a few universal graphs and curve fits. The results show the sensitivity of optimization with changes in collector parameters and operating conditions. Kovarik [26] designed an optimal solar energy collector system

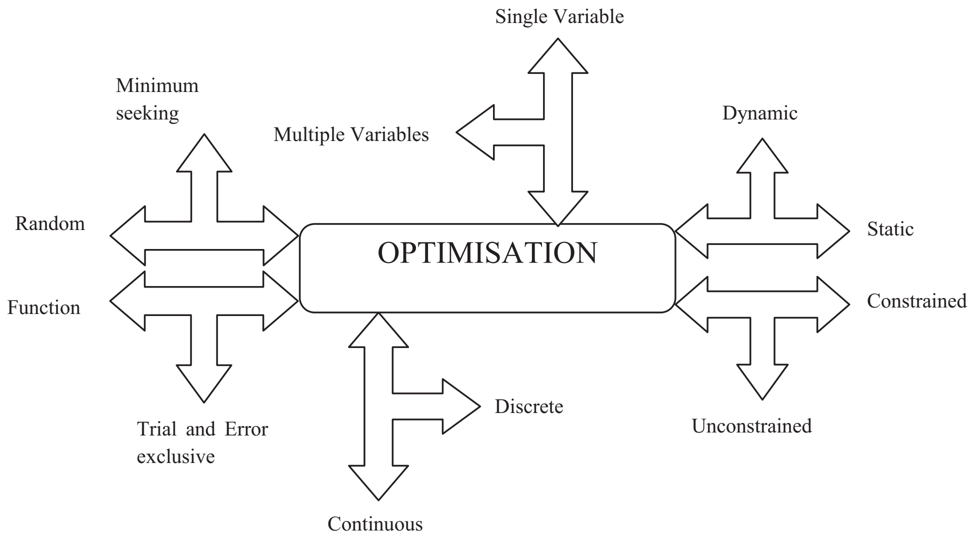

Fig. 1. Six categories of optimization algorithm [4].

considering each element has different properties which is uniformly distributed over its area and non-uniform insulation thickness. The thermal performance of solar air heater is also increased by using artificially roughness [27,28]. To fulfill the energy demands during winter and no-sun period, two or more renewable energy sources are exploited instead of increasing the rating of generating system.

3.2. Solar water systems

Gupta [29] generalizes the dynamic performance of low temperature solar energy systems considered a natural circulation type solar water heater and a basin-type solar still using response factor method on the basis of set of experimental test data. The design details of solar water heater employing flat plate collector

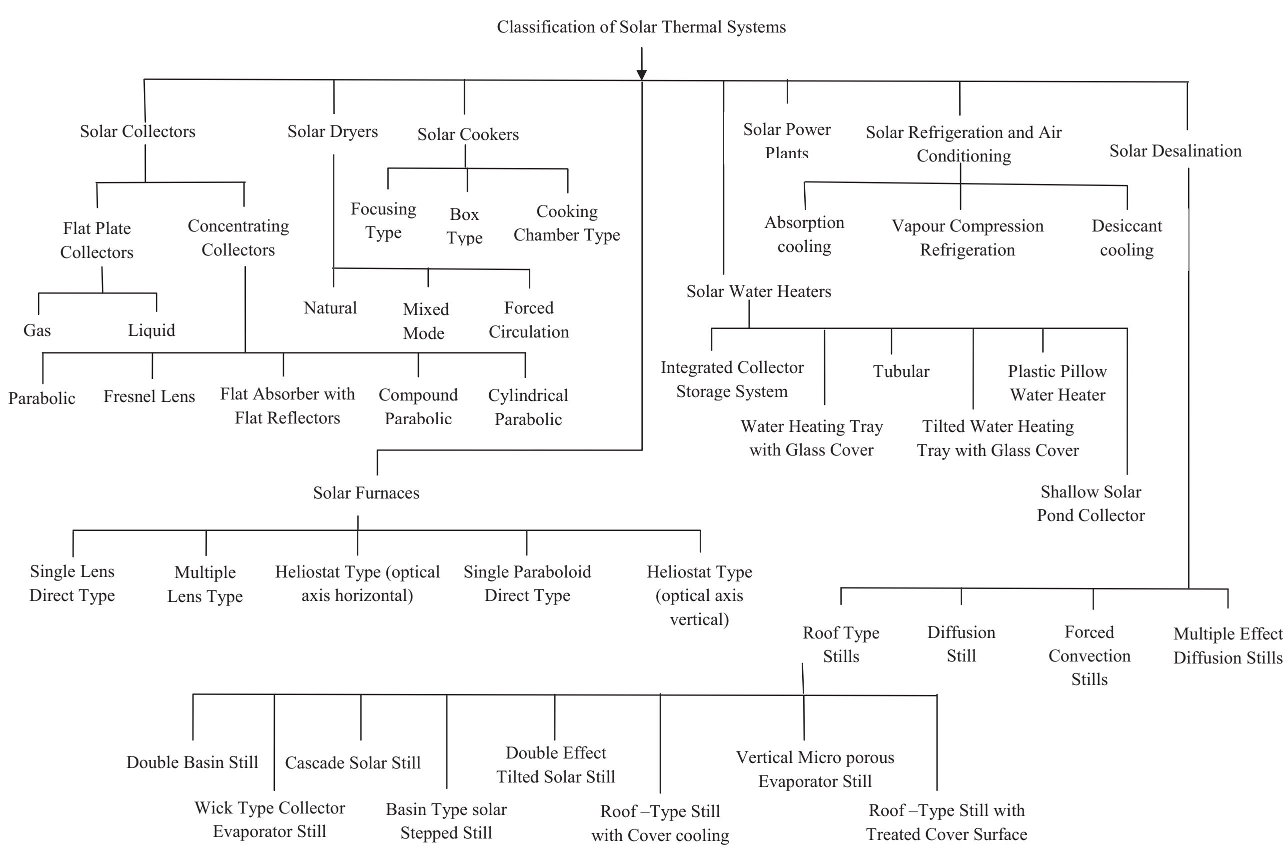

Fig. 2. Classification of solar thermal systems.

Table 1
Factors effecting thermal performance of solar systems.

Solar systems	Flat plate solar collectors	Solar stills	Concentrating collectors	Solar water heater
Factors effecting thermal performance	a. Number of glass covers plates	a. Ambient temperature	a. Aperture area	a. Hourly global radiation data
	b. Tilt angle	b. Solar radiation intensity	b. Absorber area	b. Type of surface (vertical, horizontal or tilted)
	c. Emissivity of the plate	c. Wind velocity	c. Acceptance angle and acceptance half angle	c. Meteorological data (cloud cover, wind speed and direction)
	d. Reynolds number	d. Edge and base loss coefficient	d. Theoretical concentration ratio	d. Type of insulation
	e. Liquid tubes	e. Brine depth, vapor tightness	e. Actual concentration ratio	e. Solar radiation intensity
	f. Operating conditions like ambient temperature	f. Condensate leakage	f. Solar profile angle	f. Type of collector coating
	g. Wind velocity	g. Cover slope	g. Tilt angle	g. Storage volume ratio
	h. Solar radiation intensity	h. Gap distance between water surface and cover	h. Continuous tracking about one axis	h. Effective absorptivity of solar collector
		i. Build-up of reflecting layers of salt on water surface and basin linear	i. Continuous tracking about two axis	i. Dilurnal and nocturnal relative temperature
				j. Thermal time constant
				k. Density of water

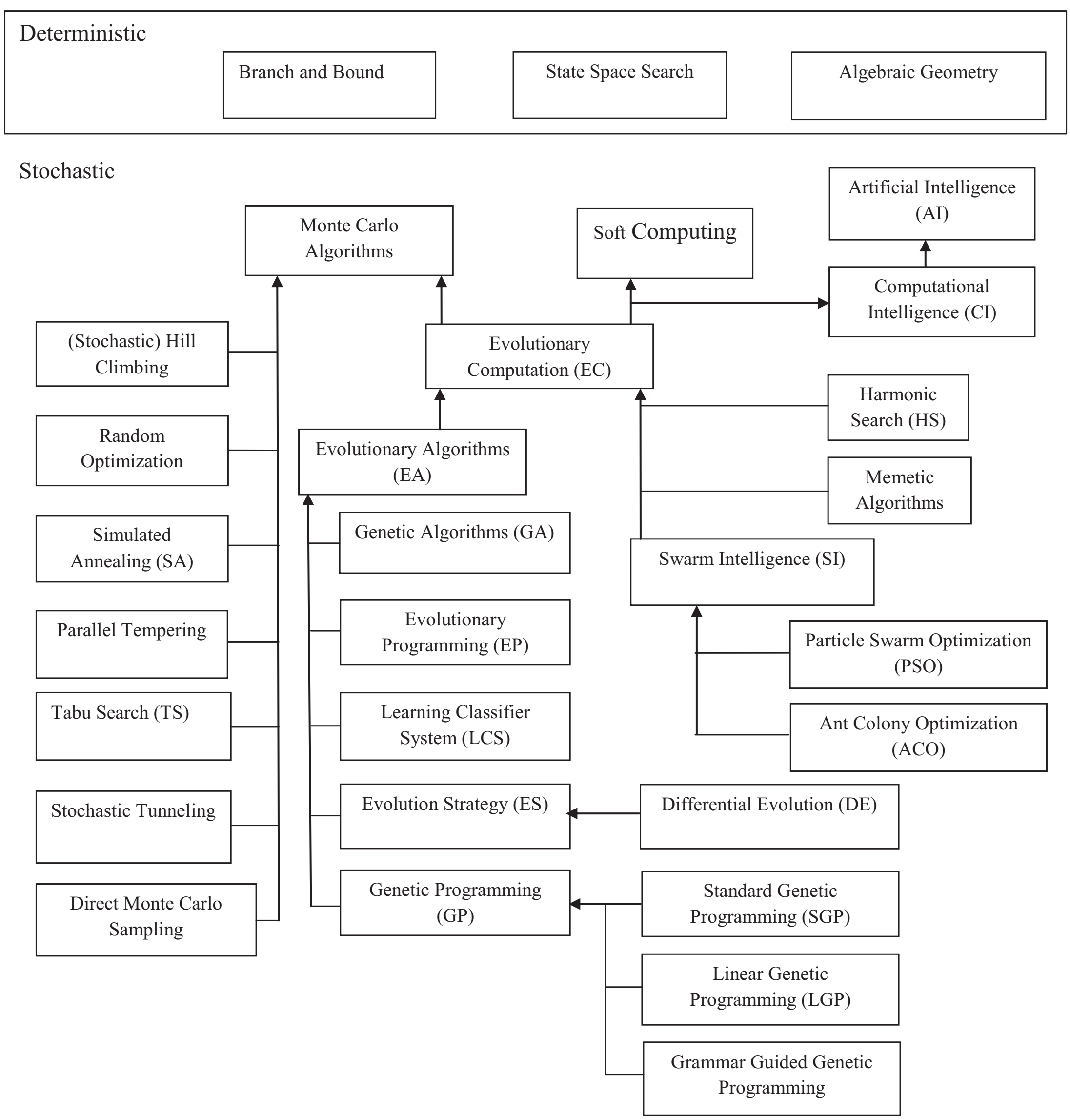

Fig. 3. Classification of global optimization algorithms [13].

consisting of wire-tied aluminium fin of 28 gauge with galvanized iron pipes for large, intermittent demands for hot water by hospitals and hostels are presented by Garg [30]. In this study, various arrangements of collectors such as series, parallel, cascade and series parallel were studied and results show that the true parallel arrangement of absorber banks yields maximum efficiency and economy, and able to heats 600 l of water up to 55 °C in winter at Roorkee. Cohen [31] also obtained the thermal optimization parameters for compact solar water heaters considering daytime heating and nocturnal cooling.

Barnes [32] proposed an approach for optimization of solar heating systems with discrete collector area. In this work a solar hot water system with monthly load of 1.18 GJ, collector with selective surface, a single low iron glass glazing is selected. The input data for calculation is taken as collector intercept and slope of performance curve are 0.718 and 4.81 W/(m^2 °C) respectively, decay constant is taken as 0.31 m^{-2} and for economic analysis, the data are collector cost per unit area is $185/m^2, unit fuel cost is 11.11/GJ, annual interest rate is 12%, year considered is 20 and annual fuel cost escalation rate is 9%. The simulation carried out on f-chart, using Oak Ridge, TN weather and solar data for a south facing collector at a tilt angle of 50°. The result shows that the optimum area is approximately 4 m^2. This study concludes that for same annual total cost, the larger area collector is selected as the discrete area collector panel. Michelson [33] has been estimated multivariate optimization for solar water heating systems. In this study collector area, azimuth, tilt, and store volume are considered as the variables. The input data used is the meteorological data, one (composite) year for Hamburg (Germany) and 1964 for Kew (UK) and the Hamburg data were formulated to form a year of 60 averaged days. The results clearly show that the optima with 60-day year are very close to those achieved with 365-day year.

3.3. Hybrid solar systems

Hybrid energy systems are more efficient, reliable and less costly than the systems that use a single source of renewable energy [34]. Odeh et al. [35] studied the effect of mismatch of pump characteristics, insolation and photovoltaic (PV) array on the performance of PV water pumping system. Glasnovic and Margeta [36] implemented dynamic optimization technique to optimize the sizing of PV irrigation water pumping systems considering all systems elements such as soil, method of irrigation, PV water pumping system, and local climate etc. Solar–wind hybrid systems were widely used and the optimization of these systems related to size and thermal performance is carried out by various reachers [37–39]. Tina et al. [40] presented a probabilistic approach to evaluate the long term performance of a hybrid solar wind power system (HSWPS). It is based on convolution technique and used for both stand alone and grid linked applications. Reliability analysis is carried out by the use of energy index of reliability and certain analytical correlations are developed to obtain power generation. Suitable probabilistic models are used to assess the performance of HSWPS for both WECS (wind energy conversion system) and PVS (photovoltaic system). In WECS, wind speed distribution and turbine output power is considered to determine power output. In PVS model the geographical location (latitude, longitude and altitude) and climatic condition (cloud cover) are the important parameters to PVS power output. The result obtained from the applied probabilistic method show agreement with the MCS for a large number of simulations run. For the application of this proposed HSWPS model, Ginostra (latitude 88.11° and longitude 15.2°) in a little Island Stromboli in Acloian Archipelago (Italy) is considered as the case study. The results show that difference between the numerical and analytical results ranges from 0.5% and 1.9%. Through the results, it is concluded that the good assessment of the long term average performance of a HSWPS can be achieved using a statistical approach rather than to time step simulation.

3.4. Other systems

Alizadeh et al. [41] works on the design and optimization of water–lithium bromide and the ammonia–water absorption refrigeration system operated by solar energy. The result shows that for fixed initial condition and known refrigeration capacity higher generator temperature results in higher cooling ratio and consequently less cost. Brooks and Duchon [42] developed a model for building heat loss on hourly variation in solar radiation and wind speed for estimating the performance of solar heating system. The input data used in this study for hourly global solar radiation on a horizontal surface taken for 13 years (1952–1964) of SOLMET [43] and hourly meteorological data related to temperature, wind speed considering direction and total cloud cover for Oklahoma City. The results were obtained carrying 172 simulations run for various combinations of house size, number of collector covers, insulation type and collector area. The numerical simulation model estimate the value of annual energy cost of $1116, solar system annual efficiency 22.30%, solar system cost $8975, auxiliary energy 5.1 MJ and annual saving $71 for collector area 100 m^2, house size of 135 m^2, insulation type II, heat loss model II and 2 collector covers. The study concludes that the performance of two models is different on daily basis but due to compensating factors, the performance on long term basis is similar.

Singal et al. [44] carried a study to satisfy the energy demands of remote small villages and islands by sustainable upliftment of renewable energy resources. Akella et al. [45] discussed social, economical and environmental effects of renewable energy systems. It discussed how clean development mechanism (CDM) enables develop countries to meet certified emissions reductions (CERs) commitments in a flexible and cost effective manner and also give direction to developing countries in meeting their development objectives. The impact of Carbon finance on plant financial rate of return (IRR) and life cycle emissions (LCE) from different energy sources are indicated in [46,47] respectively. A case study of installation of renewable energy plants which are going to be installed in zone 4 of Jaunpur block carried out [45].

4. Optimization of solar system

Nowadays, stochastic techniques are used for estimation, prediction and optimization of various solar energy systems. The researchers mainly use genetic algorithm (GA), artificial neural networks (ANN), ant colony optimization (ACO), particle swarm optimization (PSO) Simulated Annealing (SA) and other multi objective optimization techniques.

4.1. Using genetic algorithm (GA)

Genetic algorithm (GA) is one of the most popular techniques in evolutionary computation research based on the mechanics of natural selection and natural genetics. The fundamental principle followed by GA is the fittest member of population has the highest possibility (probability) for survival. Calculus based conventional optimization depends on the assumptions of continuity and existence of derivatives and the enumerative conventional techniques works on special convergence properties and auxiliary function evaluation, whereas GA works with objective function information and search for an optimal parameter set to obtained optimum value. A simple GA cycle model of population genetics is shown in Fig. 4 [48]. The GA has the following advantages over traditional techniques such as GA required only rough information about the

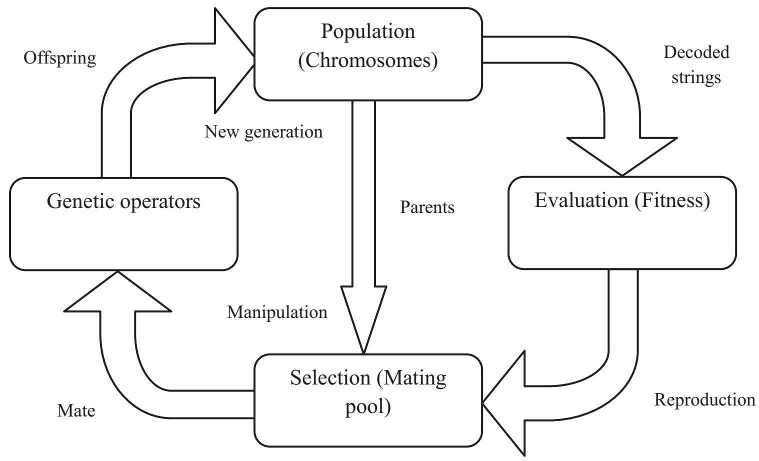

Fig. 4. The genetic algorithm cycle.

objective function and does not required the property of differentiability and convexity of the objective function, it works with a set of solutions from one generation to the next, and not a single solution, therefore it does not converge on local minima. Nowadays, GA is widely used as optimization techniques in every field. In solar systems GA is implemented to optimize the thermal performance by generating optimized set of design and operating parameters.

4.1.1. Solar air heater

Varun and Siddhartha [49] have used GA to optimize the thermal performance of flat plate solar air heater by considering the different system and operating parameters such as: Reynolds number, emissivity of the plate, tilt angle and number of glass plates. The simulation is carried on MATLAB software. The result shows that the optimized set of value is V is 2.95 m/s, tilt angle (β) is 65.33°, emissivity of plate (ε_p) is 0.86, ambient temperature is 296.11 °C and temperature rise is 2.20 °C on which optimal thermal performance is obtained.

4.1.2. Solar water systems

Loomans and Visser [50] used genetic algorithm (GA) to calculate the yield and costs of solar hot water systems based upon technical and financial data. The input data used for the optimization large solar hot water system includes population size to 10, tournament selection, two children per coupling, uniform crossover, probability of crossover is 0.50 of jump mutation is 0.02 of creep mutation is 0.04 and of inverse mutation is 0.05. The result shows the number of collectors is least sensitive to the total costs and energy gain. GA implemented on four different types of solar hot water system designs. The result with an external tap water heat exchanger shows the payback time decreases with an increasing heat demand. The result presented the applicability of GA for optimization of large solar hot water systems.

Kulkarni et al. [51] proposed a methodology to evaluate the design space for synthesis, analysis and optimization, considering various design constraints of solar water heating systems. In this research, a Pareto optimal region is identified and optimized the solar water heating system by minimizing annual life cycle cost. The input data related to load, collectors and storage used in the example for the generation of design space have been taken from an apartment building at Pune (18.53°N, 73.85°E), India. The various graphical results shows that the effect of variation of storage volume on storage efficiency, collector efficiency and solar fraction for a collector area of 80 m^2 and also the storage temperature profile for different systems configurations. The graphical explanation for complete design space and for identification of Pareto optimal curve on the design space for both unity solar fraction and different solar fraction are explained with a single day analysis. In this paper the design space for annual performance explained and obtained optimum size as collector area is 55 m^2 and storage volume is 3.1 m^3. In this research graphs related to determination of optimum solar fraction and identification of optimum design region such that the annualized cost is with 20% minimum value are drawn. This methodology enables to understand the behavior of the system with different storage volumes and area, and also useful in retrofit cases as well.

4.1.3. Hybrid solar systems

Yang et al. [52] developed an optimal sizing method using genetic algorithm (GA) to optimize the configuration of a hybrid solar power generation system using battery banks. The decision variables considered in this optimization are PV module number, PV module slope angle, battery number, wind turbine number and wind turbine installation height. In this research a case is studied to attain the climatic condition suitable for designing the project in the optimization process. The input data is chosen as the Meteorological weather year 1989 in Hong Kong. The calculation carried out for different power reliabilities (LPSP = 1% and 2%). The results shows that the hybrid solar wind system with 3–5 days battery nominal storage having depth of discharge 80% is satisfying the desired LPSP of 1% and 2% with minimum annual cost of system. The LPSP concept is a statistical parameter. Thus in a bad weather data of chosen year, the system suffer much higher probability of bring power than desired value. This study also explains that the renewable generators are oversized to meet the actual loads to compensate the performance loss due to system loss and other problems. Sacco et al. [53] evaluated the fraction of mass flow rate to be eliminated at each stage of turbines using genetic algorithm (GA). Turbines were typical pressurized water reactor (PWR). The optimization system used GA as optimization tool and PEPSE as simulation tool. The system used is basically a typical PWR secondary side having a high pressure train with two stages and a low pressure train with six stages. It also consists of reheat and regeneration. The system executed with 10 different GA seeds and 1.1529×10^{18} possible solutions were obtained. The result showed an efficiency of 35.13%, which compared with Babcock and Wilcox company having PWR ranging from 34.0 to 34.5%. The original efficiency of plant was 34.9%. Hence 0.2% efficiency gain was obtained, showing an earnings of about US $1,00,000/year. This case study has enabled to change in existing plants turbine extraction to attain the objectives of having best thermal efficiency and reducing costs of energy production. GA technique is implemented in different systems such

as: optimal sizing of stand-alone photovoltaic/wind-generator systems by Koutroulis et al. [54]. Optimization of shape of a wave energy collector to improve energy extraction by McCabe et al. [55] and maximizing the energy generation and minimizing the production cost of cogeneration systems of electricity/hydrogen by Gomez et al. [56]. In this study [54], the methodology implemented selects the optimal number and type of units conforming minimum total system cost to constraints of fulfill load energy requirement for 20 year. The proposed model implemented on a power generation system for a residential house and results are compared with conventional optimization methods like dynamic programming and gradient techniques. The simulated results also verified that hybrid PV/WG feature lower cost with respect to exclusive PV or WG.

4.1.4. Other systems

Ozturk et al. [57] developed energy input estimation equations, in order to calculate the future projection and examine the effect of design parameters on energy input of residential commercial sector (RCS). The genetic algorithm energy estimation model (GAEIEM) was used to evaluate Turkey's future energy input demand for RCS. It is based on the gross domestic product (GDP), population, import, export, house production, basic house appliances consumption and cement production. The data related to the above listed design parameters are gathered from World Energy Council-Turkish National Committee and MENR (Ministry of Ecology and Natural Resources) and Utlu from 1990 to 2023. Results obtained through three forms of GAEIEM were compared with MENR results. The comparative error for the period from 1990 to 2002 is less than 1%. This study enables the engineers, scientists and policy makers to implement energy planning studies as a potential tool. Senouci and Derham [58] applied genetic algorithm (GA) based multi-objective optimization to formulate a model. The model used to optimize the time and cost by making optimal construction scheduling plane. The decision variables used to design this model are construction method, crew formation and crew over time policy. This model implemented in three major phases that are initialization, fitness evaluation and population generation. This model has additional ability of permitting multiple resource utilization options, multiple procedure relationships and a general time cost tradeoff analysis procedure. The result of this robust multi-objective optimization model showed that how this model facilitates the construction planners to generate and evaluate optimal construction plans. This developed model capable of providing least project time for a given project cost in single run. Kumar et al. [59] used goal oriented genetic algorithm (GA) tool to generate possible optimal solutions for optimizing and evaluating various aspects related to sizing of earth to air heat exchanger (EAHX) in a non-air conditioned residential building. Various parameters such as comfort level, isothermal mass, indoor air temperature and the amount of thermal energy required for heating and cooling of building were required to specify. An 80 m EAHX system located in a hospital complex at Mathura (India) is used as an experimental data. The optimal solution obtained through GA gives inner radius is 0.2567 m, Thermal Conductivity is 0.5255 W/m°C, mass flow rate is 0.03824 kg/s, number of length segments are 91 and outer radius is 0.3035 m. The result shows good agreement with the experimental data and model predictions. Sensitivity analysis used to study the impact of humidity, ambient temperature, ground surface temperature and ground temperature at burial depth on outlet temperature of EAHX. The optimum cooling potential of EAHX at Mathura, India was found to be 38 kWh.

Sambou et al. [60] used genetic algorithm to maximize both thermal insulation and thermal inertia. In this work, quadrupoles method was used to calculate the thermal capacitance that quantifies the inertia of wall. In this research, three case studies which are having N parallel layers of homogeneous and isotropic materials with fixed wall thickness ($h_w = 0.4$ m). The first case study result showed that the massive material has wavelength ($\lambda = 0.144$ m) and the optimal thickness of insulation is $\lambda/4$. The ASHRAE database for wall materials has been used for boundary values of thermo-physical parameters. The second case study is about determination of optimal composition of a wall made of ASHRAE material having fixed thickness. The result showed that the optimal position of the insulation is at wall outdoor side and another examined that no need of massive layer thickness greater than $\lambda/4$ to improve wall thermal inertia. The result of third study showed that most Pareto optimal walls having two or three layers instead of fixed five layers and also the thermal resistance increases linearly with thermal insulation. The results from these optimization studies can be utilized in dealing with buildings energy consumption and comfort. Future research will carried out on the impact of optimized walls on the behaviors of buildings. Some additional criteria related to climate or occupation schedule can be used to choose among multiple Pareto Optimal solutions. Congradac and Kulic [61] used GA to control CO_2 concentration in HVAC (heating, ventilation and air conditioning) to optimize power saving with MATLAB Simulink and verified by energy software. Wright et al. [62] implemented multi-objective genetic algorithm (MOGA) for optimization of building thermal design and control by identification of optimum pay-off characteristics between energy cost and zone thermal comfort.

4.2. Using particle swarm optimization (PSO)

Particle swarm optimization (PSO) has a great potential to solve optimization problem. Kennedy and Eberhart [63–65] proposed this technique in 1995 and implemented as a simulation of a simplified social system in which each member of school take benefit from the discoveries and past experience of other members [65]. In this optimization technique, the potential solutions, called particles, achieved the best fitness of the particles in the problem space.

PSO is very fast, efficient and effective when implemented to a diverse set of optimization problems. In PSO technique, particles, i.e. the potential solutions are flown through the desired problem space as given in problem by following the same root as followed by the current optimum particles. The best solution (fitness) has been achieved by the particles. In this, each particle has memory, which makes them to remember the best solution in the feasible search space and this value is known as personal best (pbest). The particle swarm optimizer achieve another best value which is the best value attained by any particle so far in the neighborhood of the particle and known as global best (gbest).

4.2.1. Hybrid solar systems

Hakimi and Tafreshi [66] applied particle swarm optimization (PSO) to unit sizing of a stand-alone hybrid power system and to optimize sizing of a stand-alone wind fuel cell hybrid power system for Kahnouj area in South East Iran [67]. The objective of this [89] study is to minimize the total costs of the hybrid power system such that the demand of residential area is met. In this work, biomass is used to provide Hydrogen. The model considered for study consists of Bergey Wind Power's BWC Excel-R148, Ballard fuel-cell, Avalence electrolizer, MAHLER reformer, hydrogen tank and anaerobic reactor to produce Methane. The inputs of optimization procedure are capital costs, operation and maintenance costs, efficiency, replacement costs, life time of components and project, component's specifications information about area's population and produced waste. The simulation results show that the nominal power 7.5 kW for each wind turbine and 1 kW for each fuel cell and electrolizer, size of hydrogen tank is 1 kg, and project's life time is 20 years. The results presented the optimal sizing of wind turbine, electrolizer, hydrogen tank and fuel cell is 687, 2504,

2810, 1222 respectively and optimal cost is $35.5M. The size of reactor, reformer and compressor are equal to 750 kg/day, 31.2 kg H_2/day, and 50 kW respectively and are fixed. The life time of wind turbines are more and that's why decreases the project costs. This hybrid system is suitable, where wind speed, availability of large agricultural land waste and fuel transmission costs and pollution high. Standard PSO has the problem of premature convergence in some of the optimization problems, hence modified PSO like hierarchical PSO, CPSO etc. are implemented. Airashidi and Naggar [68] proposed PSO to minimize error associated with evaluated model parameters for annual peak load forecasting in electrical systems. The input data employed in this study is actual recorded data from Kuwaiti and Egyptian networks. The results are compared with the well known least square techniques and produced better estimates. Hence PSO technique is quite promising and used as a tool for parameter estimation.

4.2.2. Other systems

Azadani et al. [69] deals with the multi product and multi area electricity market dispatch problem using constrained particle swarm optimization (CPSO). Three case studies are examined to verify the efficiency and effectiveness of the proposed CPSO. In first case study, an economic load dispatch problem solved by three generating units with quadratic cost function and the result obtained are similar to standard PSO. But this proposed new model CPSO also used for complex problems. In second case study, a system with six generating units is studied. The result shows that the total market cost increases up to $105.9 more if transmission capacity effects are considered. Third case study includes 13 generating units with valve point loadings and also modified to study the behavior of valve point with multiple fuels. The result shows if a contingency occurs in system, then the total market cost increases. The result obtained by CPSO compared with the results calculated by other method. These results are similar and the proposed method also is applicable to complex problems. Park et al. [70,71] implemented PSO for economic load dispatch with non-smooth cost function.

Kongnam and Nuchprayoon [72] formulated a nonlinear programming problem of estimation of rotor speed and tip speed ratio to maximize the power and energy output from the wind turbine using PSO. The Weibull shape and scale parameters are assigned to wind data and variability nature of wind. In this work, the wind speed data measured for two years (2005–2006) at height of 36 m from a meteorological station on an hourly basis at Promthep cape, Phuket, Thailand. The Weibull distribution obtained using standard deviation method and also find by a variety of methods [73]. The results obtained for differences in energy yields under fixed and variable-speed operations are compared, when Weibull distribution shape parameter changes from 1.8 to 2.8 at constant scale parameter of 5.0 then differences in energy yields changes from 18.15% to 12.16% and when Weibull distribution shape parameter kept constant at 2.0 and scale parameter changes from 2.0 to 7.0 then differences in energy yields changes from 19.01% to 5.13%. Hence the comparison concluded that the energy produced by variable-speed wind turbine is always higher than fixed-speed wind turbine and the optimum rotor speed and optimum tip speed ratio is more dependent on Weibull scale parameter than shape parameter.

Lee and Lin [74] have implemented particle swarm optimization technique to minimize energy consumption of multi chiller system. The concept of decoupled systems has been illustrated in detail in ASHRAE Handbook [75]. Two case studies are carried out one for a semiconductor plant in Hsinchu Science based Park, Taiwan having multi chiller system composed of three 800 RT units and other for a hotel in Taipei having multi chiller system consists of two 450 RT and two 1000 RT. The results of two case study enlightened that PSO estimated minimum energy consumption at low demands and thus overcome the shortcomings comes in genetic algorithm and Lagrangian method. Fong et al. [76] has implemented heuristic optimization method incorporating non-revisiting strategy to improve optimization effectiveness and reliability and evaluate fitness value with minimal computer memory, detect the revisits and escape from re-evaluate. The results of this study conclude that the non-revisiting genetic algorithm and non-revisiting PSO search better solution than conventional GA and PSO at a limited number of function evaluations in case of central air conditioning systems. The non-revisiting has been implemented in heuristic optimization such as PSO, GA and simulated annealing [77–79]. Niknam and Firouzi [80] developed an algorithm based on the combination of Nelder-Mead simplex search and Particle Swarm Optimization algorithm to present a practical distribution state estimation (DSE) including RESs. The proposed algorithm is called PSO-NM and find load and RES output values by weighted least square (WLS) approach. The available input data for constant load and RESs, power factor, set point of VRs and local capacitors are used. In this work, a 70 bus test feeders, 8 RESs and 8 variable loads and 8 measurement devices installed on buses 1, 70, 6, 10, 18, 25, 47 and 40. These devices are Ammeter and Voltmeter. The result shows that the best value of c_1 is 2, c_2 is 2, w_{min} is 0.4, w_{max} is 0.9 and N_{swarm} is 20. The comparison of the best and worst solutions of the proposed algorithm with other corresponding method high lightened the effectiveness of the proposed optimization technique. The results explain that the standard deviation of the proposed algorithm is less than others and leads to better solutions. The PSO-NM based algorithm can handle non-differential and non-continuous objective function of DSE and it could also be used for a wide variety of optimization problems.

4.3. Using simulated annealing (SA)

Simulated annealing (SA) was independently introduced by Scott Kirkpatrick, Gelatt, Vecchi and various other authors in 1980s. This process is based upon the annealing process in the statistical mechanics which obeys first law of thermodynamics and specifically proposed for discrete optimization problems and later successfully implemented to continuous problems and complicated combinatorial problems. It proves to be effective and efficient in network reconfiguration problems and with the increase in system size its search capability increases. With the help of a smoothing strategy, SA becomes able to escape easily from local minima and quickly reach in the vicinity of an optimal solution.

The SA has following advantages such as, capability to deal with arbitrary systems and cost functions, ability to refine optimal solution, and easily implementation even for complex problems. The major limitation of SA optimization technique is repeated annealing and it is unable to tell whether the obtained solution is optimal or not. SA has been applicable to various power system applications like unit commitment, transmission expansion planning, maintenance scheduling, etc.

4.3.1. Hybrid solar systems

Ekren and Ekren [81] used SA algorithm for optimization of a PV/wind hybrid energy conversion system with battery storage. The utilized algorithm is a heuristic approach and based on stochastic gradient search for global optimization. The objective function of this study is the minimization of total cost of the system, having decision variables like PV size, battery capacity and wind turbine rotor swept area. In this study, random simulation is carried out by using probabilistic distribution for hybrid system. This algorithm is implemented on a stand-alone hybrid system using the historical mean solar radiation and wind speed data for the period of 2001–2003 recorded at meteorological station to meet the electricity demand of a global system for mobile communication base

station on a campus area, in Turkey. The simulation and optimization has been carried using commercial software ARENA 12.0. The convergence of the simulation results are obtained after 127th iteration with optimum value of PV area is 3.13 m^2, wind turbine rotor swept area is 32.6 m^2 and battery capacity is 35.12 kWh. These results led to total cost of $33,283.6 for hybrid energy system. The results are compared with other response surface methodology (RSM) results [82,83] and 10.13% improvement is obtained. This study enables to achieve optimum points at a reasonable time in a large search space.

Mitchell et al. [84] used a simulator to evaluate energy flows on an hourly basis of a renewable energy system in Western Sydney area. In this model, the potential gains of using predictive procedures also demonstrated. In simulation part, three main studies have been carried out. First study assumed full renewable energy some with no standby, second study assume the availability of standby plant and third study assumed grid connection. These studies enlightened the use of predictive controller to control import and export switching for the optimization of grid loading. The data is available for a period of 1997–2000 in Perth of Western Sydney was compared with predictive routine and a saving of 15% was observed. The model used in this study is able to demonstrate all system design issues related to minimum capacities, benefit of predictive controllers and rapid decreasing benefits of additional capacity. Hui [85] developed a multi objective optimization technique to optimize the key components in hydraulic hybrid vehicle (HHV). It is based on adaptive simulation annealing genetic algorithm (ASAGA) and proposed to find design parameters for maximum fuel economy. The basic parameters of HHV used in simulation are as follows: vehicle mass is 9700 kg, rolling resistance coefficient is 0.009, vehicle front area is 4 m^2, body aerodynamic drag coefficient is 0.335, wheel radius is 0.48 m, final derive ratio is 5.286, maximum speed and grade ability are greater than or equal to 90 km/h and 30% respectively. In this study, all weighing factors can be set different values as per the need. Finally the result shows that the key components size and position of optimal parameters of HHV, increases the thermal performance and minimizing the final consumption. From the above studies the SA has following promising features: low algorithm complexity, potential to obtain global optimal, required very less model treatment and not much affected by discontinuities in system model and has disadvantage of low computation efficiency as compared to successive quadratic programming and the convergence of the SA is not as fast as genetic algorithm [85].

4.3.2. Other systems

Faber et al. [86] implemented simulated annealing for the dynamic optimization of energy and chemical engineering processes. In this study, simulated annealing technique is applied in a set of MATLAB script files with graphic user interface (GUI). Various case studies such as: batch reactor optimization and simplified combined-cycle power plant with penalty and no penalty terms are performed using SA. The result shows that initial annealing temperature is very vital and it is problem specific parameter in SA.

4.4. Using multi-objective optimization technique

4.4.1. Hybrid solar systems

Yang et al. [87] optimize the capacity sizes of various different components of hybrid solar wind power generation having a battery tank. For this a hybrid solar wind system optimization sizing (HSWSO) model was developed. This model consists of three major parts. First the model of hybrid system, second the model of loss of power supply (LPSP) and third the model of the Localized Cost of Energy (LCE). In modeling of wind energy conversion system there are three main parameters. The parameters are wind turbine, wind speed distribution and hub height of the wind tower. In this study, boost rectifier efficiency is 95%, the proposed average approximation for the accumulated charge and the battery state of health is 0.02%, depth of discharge (DOD) is 30%, inverter efficiency is 92% considered to be as an input. A case study of the simulation model is carried out by running the HSWSO program. This case study is about supply power for a telecommunication relay station on a remote Island in Shanwei of Guangdong Proviance, China. According to the project requirement and technical considerations, 1000 W as chosen the demand load, whereas the demand load includes 700 W, carrier wave (220 V AC) and 55 W microwave (24 V DC). The result shows that the optimum configuration for an LPSP of 5% occurs when the battery tank used 10 batteries, which mean 50% capacity of one day's power consumption by the demand side. For more reliability more batteries are used and hence high cost. Fong et al. [88] developed solar-assisted desiccant cooling system (SADCS) to handle the cooling load of typical office in Hong Kong using a robust evolutionary algorithm. The simulation model of SADCS was developed by using TRNSYS 16.01 and component library TESS. The inputs and parameters of SADCS used in this study are taken from Hong Kong Typical Meteorological Year in the Energy Plus/ESP-r format (.epw). The SADCS was designed to handle the cooling load of an office with conditioned space of 196 m^2 and 3.6 m high from 08:00 to 18:00. The results obtained from simulation showed that the range of monthly average solar fraction was from 8% to 33% and yearly average was 17%. The monthly average and mean COP was from 1.08 to 1.60 and 1.38 respectively. The simulation results obtained present in graphical form, which shows the solar air collector provides the desired thermal energy with a minimal contribution of auxiliary heater. This SADCS has advantage of energy efficiency and indoor air quality and solar cooling would provide green solutions for buildings. Fraisse et al. [89] implemented a new global evaluation technique and compare study of various optimization criteria for SDHWS.

4.4.2. Other systems

Vargas et al. [90] implemented global optimization on a solar collector driven water heating and absorption cooling plant and simulate the model for transient and steady state response for different operating and design condition to optimize maximum performance with minimum system pull up and pull down times and maximum second law efficiency. The 4th and 5th order Runge–Kutta method is used for numerical simulation and the values of maximum solar irradiation taken from [91]. The result shows that with 25% the variation of performance in the range of $0.096 \leq \Psi_{H,s} \leq 0.335$, maximum sharp is obtained and the optimal set of three dimensionless heat capacity rates are nearly (1.43, 0.23, 0.14) for obtaining maximum second law efficiency. The following conclusions were drawn from this study: (a) Existence of optimal set of values for the three heat capacity rates such that the proposed model produced maximum energy input rate. (b) The proposed model could be implemented to locate different design parameters, to obtained maximum second law efficiency. (c) The optimized values found for the objective functions are sharp, therefore must be identified accurately and efficiently. Optimization technique also used in hybrid ocean thermal energy conversion with an offshore solar pond (OTEC-OSP) to optimize cost and increase efficiency by Straatman and Sark [92], for optimal sizing of photovoltaic (PV) irrigation water pumping systems by Glasnovic and Margeta [36], and energy consumption optimization in buildings in which hydrosolar roof integrated with air conditioning system by Lucas [93].

McCorkle et al. [94] proposed a novel technique by modifying roulette selection with feature weighted general regression neural network to decrease the computation time for evolutionary optimization of systems model using CFD. Lambert and Hittle

Table 2
Comparison of thermal performance using various optimization techniques for flat plate solar air heater.

Author and year	Parameter considered	Technique implemented	Net outcome (at $I = 800\,\mathrm{W/m^2}$, $\Delta t = 10\,^{\circ}\mathrm{C}$)	Comments
I. Altfeld (1988) [26,27]	Ambient and operating conditions like solar radiation intensity, wind velocity, area ratio, ambient temperature, mass flow rate, geometry of duct, roughness and type of fins	Second law optimization	$\Delta\eta_{th}$ = Thermal performance − $\Delta\eta_{th}$ = 1.7% (wind condition)	I. Thermal performance and net energy increases with increase in area of fins and with low heat transfer coefficient. II. With increase in Re only 5% net energy flow more is obtained but system cost increases effectively. III. Artificial roughness of plate increases net energy flow.
II. Kalogirou (2006) [98]	Wind and no wind condition, collector time constant, collector stagnation temperature, incidence angle modifier coefficient at longitudinal and transverse direction, collector heat capacity	ANN	$\Delta\eta_{th}$ = 4.5% (no wind condition)	I. Satisfactory accuracy and further increased by using more cases to trained the network. II. Using fluid content and absorber mass data for all collectors, then more accurate results are obtained.
III. Varun and Siddhartha (2009) [58]	Reynolds number (Re), emissivity of glass plate (ε_p), tilt angle (α), No. of glass covers plate (N), wind velocity, solar radiation intensity, ambient temperature	GA	$\Delta\eta_{th}$ = 8.6%	I. With increase of Re, N, and t_a the thermal performance increases. II. With increase in solar radiation intensity, thermal performance decreases.

[95] presented a computational tool which is based on combinatorial optimization technique to design a near optimal autonomous power system for electrification system of remote village for the given set of demand points. The results of the lower level are obtained through different algorithms, i.e. lower level exhaustive enumeration algorithm, greedy algorithm and simulated annealing algorithm. The results from different algorithm are compared and concluded that the greedy algorithm provides global optimal configuration for the special case of uniform load size and no effective maximum length constraint whereas for this set of tests, the configuration produced by simulated annealing are never more than 2.2% higher in cost. If comparison tests performed considering low voltage length constraint and non-uniform load sizes, then simulated annealing is preferred. Results of the upper level algorithms are obtained by combining the upper level exhaustive algorithm and upper level simulated annealing algorithm with any of the three lower level optimization techniques. The two stage algorithm is used to solve the optimization problem and the results obtained show that the total cost of solution did not deviate by more than 1.2% from that of annealing/annealing algorithm for any 100 tests performed. The two stage algorithm takes less computation time and better speed of optimization as compared to annealing/annealing algorithm. The computation time taken by Pentium PC, for tests on villages having up to 250 demand nodes was typically 5–20 min (Table 2).

Diakaki et al. [96] used multi objective techniques to improve the energy efficiency in buildings and provide maximum alternative solutions. The problem studied consists of an insulation

Table 3
Comparison of various studies carried by implementing different optimization techniques for solar water heater system.

S. no.	Author and year	Parameter used	Technique implemented	Comments
1	Tzafestas (1974) [17]	Cold water flow rate, distance between collector and hot water tank, insulation, ambient temperature, solar heat energy	Finite difference modeling and linear regression	I. The maximum difference between average temperature of water in heat exchanger and in hot water tank obtained when flow rate interior of solar water heater is in vicinity of zero. II. The work can be extended further towards estimating a time varying model to evaluate better results.
2	Michelson (1982) [33]	Collector area, store volume, meteorological data for Hamburg (Germany) and 1964 for Kew (UK), tilt, azimuth	Simplex method	I. Simple payback period is used as optimum criteria for the economic optimization. II. Optimum collector tilt was around 5° less than the altitude.
3	Kalogirou (1999) [69]	Collector area, storage volume, type of system, storage tank heat loss coefficient, tank type, solar irradiation, mean ambient temperature, initially water temperature in storage tank	ANN	I. Due to learning capability of network, the performance can be increased if collector performance characteristic data is available. II. High speed, simplicity and ability to learn enhanced the potential and performance as compared to conventional algorithmic methods.
4	Loomans (2002) [49]	Number of collectors, collector type, collector heat exchanger area, heat storage mass, number of heat stores	GA	I. Fractional energy saving decreases as the tap water draw-off increases, thus decrease in relative contribution of solar energy to total heat demand. II. For large solar hot water system, payback time reduces with increase in heat demand, when an external tap water connected with it.
5	Fraisse (2009) [89]	Collector area, solar radiation intensity, tank volume, thermal losses, financial cost	New global evaluation	I. Solution obtained is not ideal due to size restrictions related to available material, not realistic and not considering the technological precautions. II. Add various parameters to enhance the performance like thickness of insulating material, height of auxiliary heater in tank etc.

Table 4
Comparison of results obtained by different optimization techniques in case of hybrid solar–wind systems.

Author and year	Parameter Considered	Technique Implemented	Net Outcome	Comments
a. Tina et al. (2006) [43]	Wind speed distribution, turbine output power, geographical location (latitude and altitude) and climatic condition (cloud cover).	Probabilistic optimization based on convolution technique	Difference b/w analytical and numerical result ranges from 0.5% to 1.9%	I. Proposed relationship between various system parameters. II. Statistical approach produced good results related to long term performance of hybrid solar system.
b. Koutroulis et al. (2006) [60]	PV modules tilt angle, type of PV module, installation height of WGs, DC/AC inverter type, daily radiation, battery type and nominal capacity, hourly mean values of temperature, and wind speed.	GA	Difference of hybrid results with WG and PV produces saving of 14.4% and 57.52% respectively	I. Reliable power supply under different atmospheric conditions. II. Estimated optimal number and type of every individual component such that zero load rejection. III. Lower system cost as compared to either wind generation (WG) or PV sources.
c. Hakimi and Tafreshi (2009) [66]	Wind turbine, fuel cells, a reformer, DC/AC converters, hydrogen tanks, an electrolyte.	PSO	Optimal cost $35.5M	I. High reliability due to fuel cells,. II. Storage components solve the problem of dependence of renewable energy sources on the environmental conditions. III. Model suitable where appropriate wind speed, high fuel cost and huge agricultural waste is available.
d. Ekren and Ekren (2010) [81]	PV size, wind turbine rotor swept area, solar irradiance, wind speed, electricity consumption, battery capacity.	SA	10.13% improvement	I. To optimize an energy system having different decision variables and large search space, SA with heuristic approach estimated optimum results in reasonable time. II. This study further extended using inflation rate as one of the parameter which effect total cost.

provide by gypsum board. The aim of this study is to decrease the acquisition costs and to improve the resulting energy savings with constant choice for the window type, walls insulation material and thickness of wall insulation layer. This problem programmed in LINGO software using three multi optimization techniques that are the compromise programming, global criterion method and the goal programming. The problem studied is a naïve one, whereas a real problem is far more complex and complicated. In such cases more sophisticated techniques then those presented here is used and raise direction for future work. The study concluded that to achieve improvement in the energy efficiency of building and the quality of the indoor environment, the DM has to compensate energy, financial, environmental and social factors. Means the real world energy efficiency improvement processes have inherent difficulties which complicate both modeling and solution approach. Therefore more investigation is required to handle the problem of improving energy efficiency in buildings as a future research work with its real dimensions. Kalogirou [97] used artificial intelligence methods such as ANN and GA, to optimize solar systems. The results obtained from TRNSYS are used to train the ANN and developed a correlation between collector area and storage tank size from which life cycle savings can estimate. Genetic algorithm is implemented to evaluate the optimum size of these to parameters, for maximizing the life cycle savings. In this study, the present methodology had been implemented on an industrial process heat system having flat plate collectors and results show an increase in life cycle savings of 4.9% and 3.1% for subsidized and non-subsidized fuel prices respectively. Kalogirou [98] implemented ANN for the estimation of performance parameters of flat-plate solar collectors. In this study, Six ANN models were proposed for the estimation of collector coefficients, both at wind and no wind conditions, collector time constant, collector stagnation temperature, incidence angle modifier coefficients at transverse and longitudinal directions, and collector heat capacity. The input data for training, testing and validation of ANN are obtained from LTS database, which consists of data of 130 thermal solar collectors and the database also includes a number of data taken from testing solar collectors at the SPF laboratory in Switzerland. The results obtained through ANN is compared with actual experimental values and found the differences in incidence angle modifier are very small (maximum 0.0057), maximum difference in collector time constant is equal to 4.2 s, the maximum difference in stagnation temperature is 6.6 °C or 3.2% and for collector heat capacity is 1.38 kJ/K. The maximum differences in thermal performance for temperature difference of 10 °C and 50 °C at wind condition are 1.7% and 1.9%, and at no wind condition are 4.5% and 4.5%. The accuracy of estimation can be increased by using more cases to database, because the network has the capability of learning from new examples.

5. Discussions

To improve the thermal performance and obtain optimized set of operating and design parameters a number of stochastic optimization techniques are implemented as studied in the literature. In case of solar air heater, the thermal performance optimization is carried out using different optimization techniques such as genetic algorithm [49], artificial neural networks [98], second law optimization [21,22], mathematical optimization techniques [23] and experimental values [24] and obtained a set of optimized parameters. The result shows related to the value of thermal performance obtained using various optimization techniques and experimental are compared for 10 °C rise in temperature and at solar radiation intensity (I) equal to 800 W/m^2 as shown in Table 3. Where as the model used by Kalogirou [44] show that the difference in thermal efficiency (ANN results and experimental results) is 1.7% at wind condition and 4.5% at no wind condition for 10 °C rises in temperature. Hence above comparison conclude that the stochastic optimization technique gives results for variable values of operating parameters whereas experimental results are based on fixed values of operating parameters. Stochastic optimization techniques

have the ability to converge to optimal points within reasonable time in large search space and various decision variables.

Some studies related to the optimization of solar water heater system from different authors using different deterministic and stochastic techniques are listed in Table 3. The results indicates that for the Distribution state estimation (DSE) problems [80], the proposed algorithm PSO-NM produce effective, efficient, reliable, high quality solution and fast computation as compared to original PSO, HBMO, ACO, GA and NNs. For the optimal design parameters and energy management of centralized air-conditioning systems the proposed strategy [79] NrGA and NrPSO generate better results than conventional GA and PSO. Various techniques such as experimental results, global evaluation technique [89] and simplex method [33] are implemented to improve the thermal performance and design parameters of solar water heaters.

In case of Hybrid solar–wind systems, the different optimization techniques are implemented to achieve optimal design and operating parameters for attaining optimal size, low system operating and maintenance cost and better life time of system as shown in Table 4. From the comparison shown in Table 4, it is clear that the hybrid systems have the advantage of reliability, reduce environmental effect on renewable system and also provide better results in terms of saving than exclusively either wind generation or photovoltaic. Stochastic techniques such as simulated annealing (SA), ant colony optimization (ACO), genetic algorithm (GA) and other multi-objective techniques are implemented on different models and still required to implement all techniques on a single model to compare the results of various techniques and knowing which techniques provide optimum results for which system. The combination of two or more techniques also provides optimum design and optimal set of parameters for a specified objective function. But from the literature it is clear that the stochastic optimization techniques generate better results as compared to experimental and produce optimum operating and design parameters which ultimately help in economic, social and environmental growth.

6. Conclusions

In the present study, a review of stochastic techniques used in solar systems has been carried out and the results obtained from different techniques for same solar system are compared. From the review, it is clearly indicated that the use of stochastic techniques results in achieving substantial improvement in the efficiency and reduction in total cost of solar systems by selecting the optimal set of design and operating parameters for the solar systems. The stochastic techniques use a range of operating and design parameters to estimate the thermal performance or to achieve the objective of the study, hence by selecting optimum parameters set the corresponding optimum results can be obtained. From the discussion, it is observed that the comparison of various optimization techniques either used single or in combination give better results as compared to experimental results. PSO, SA and ACO implemented in hybrid solar systems but these optimization techniques can also be applied on solar air heaters and solar water heaters and other solar systems. In solar systems optimization, there is a lot of scope for using combination of techniques in order to achieve optimal thermal performance of the solar systems with optimum operating and design parameters. Further the study can be extended to estimate life cycle savings (LCS) and thermal performance optimization for solar energy systems either individually or in hybrid from.

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